Trabajo 3

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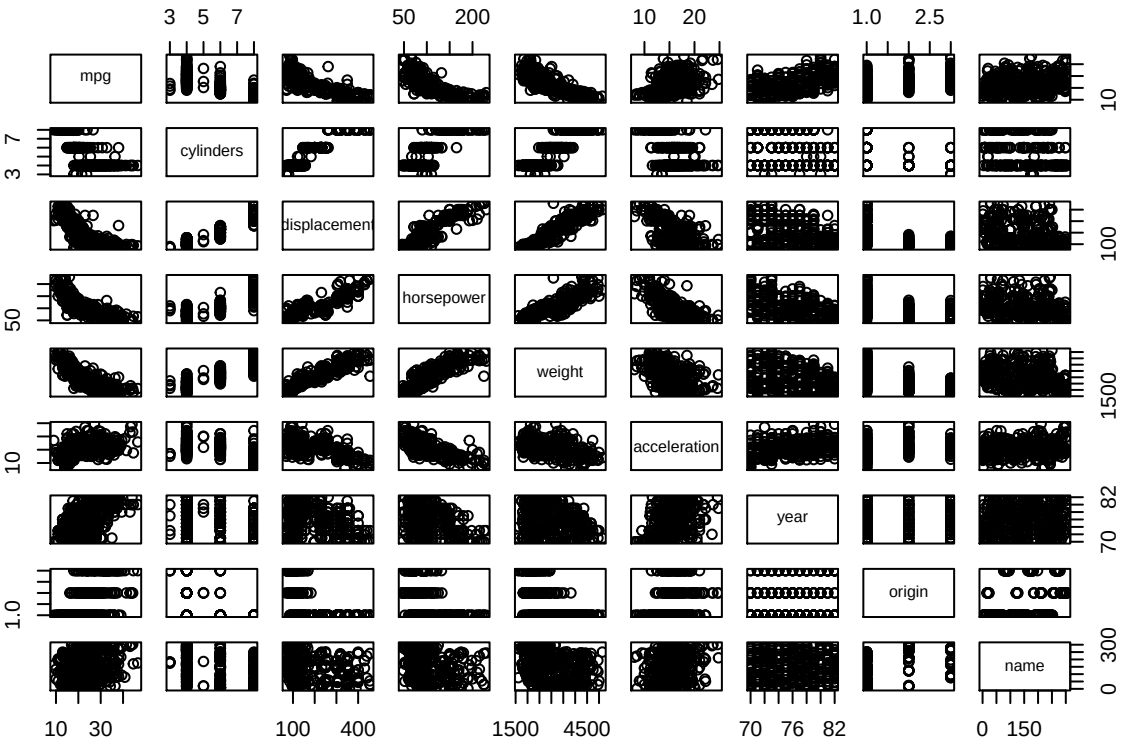
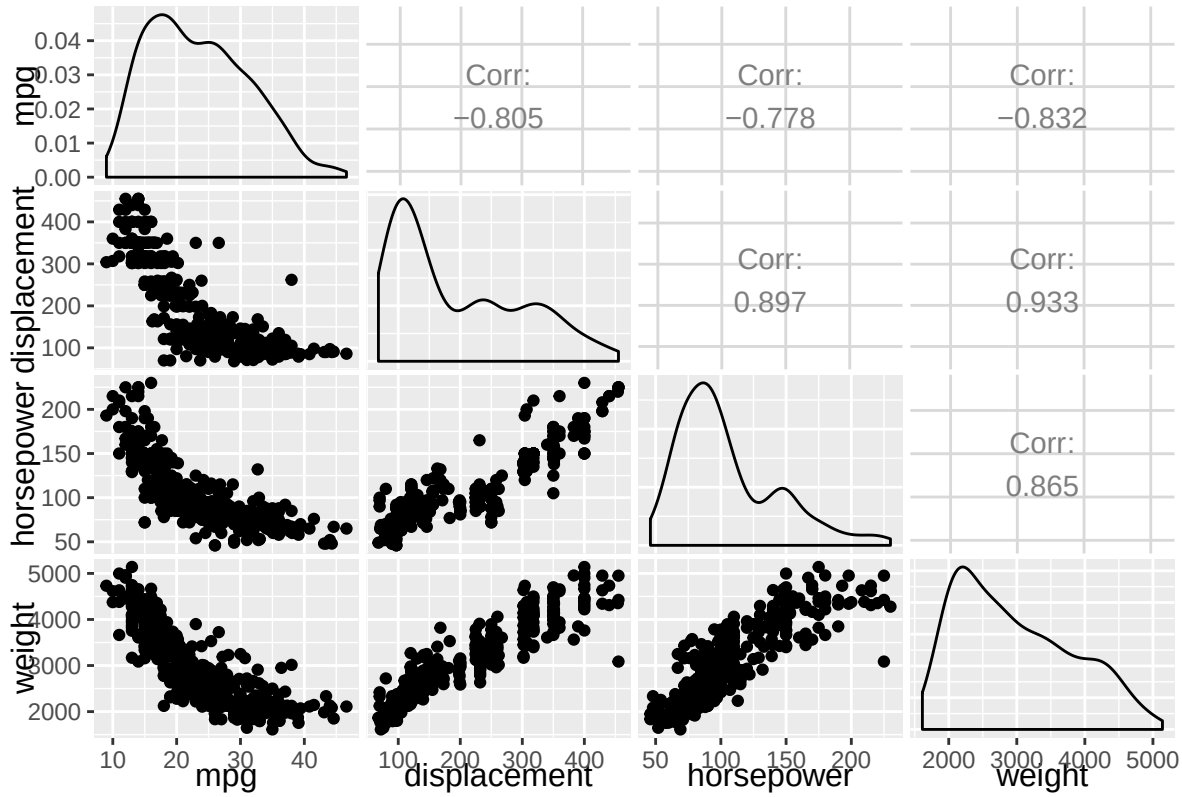
Ejercicio 1

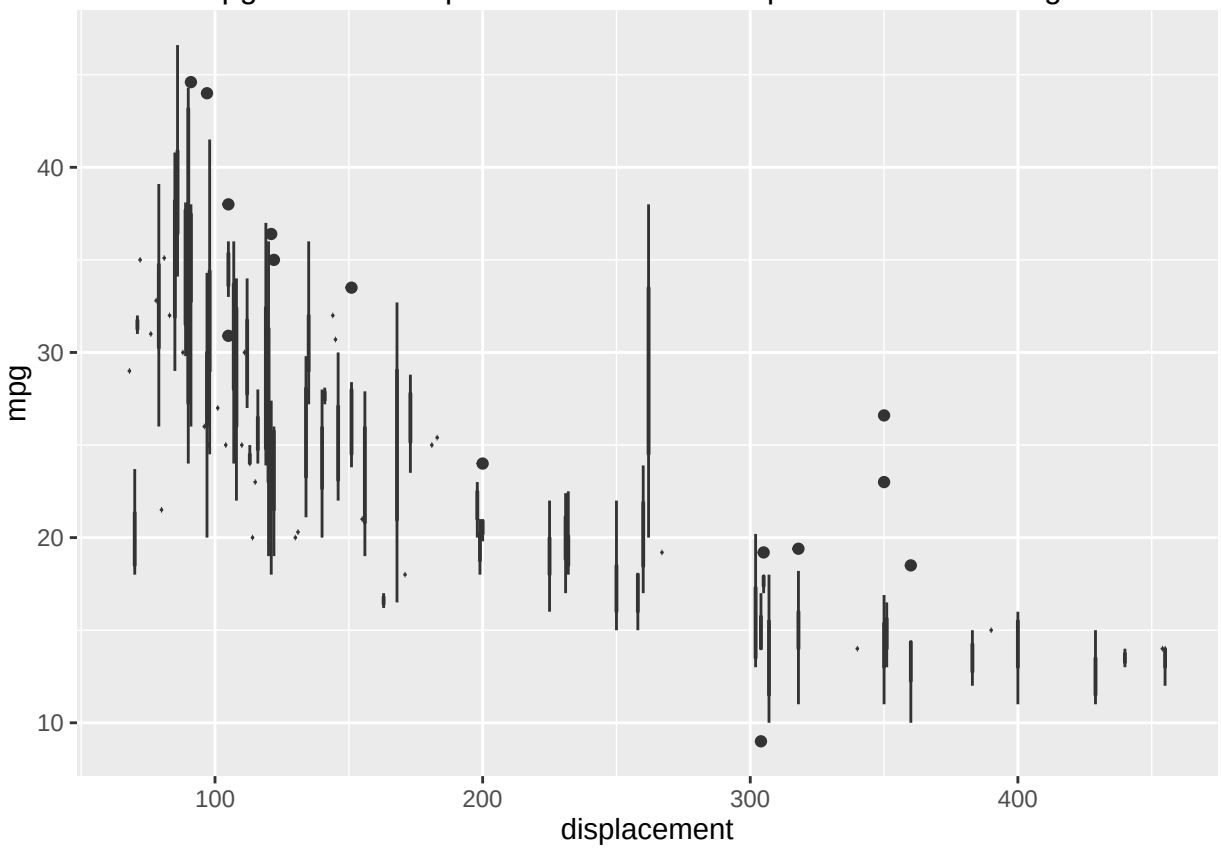
```
## The following object is masked from package:ggplot2:
##
##     mpg
```

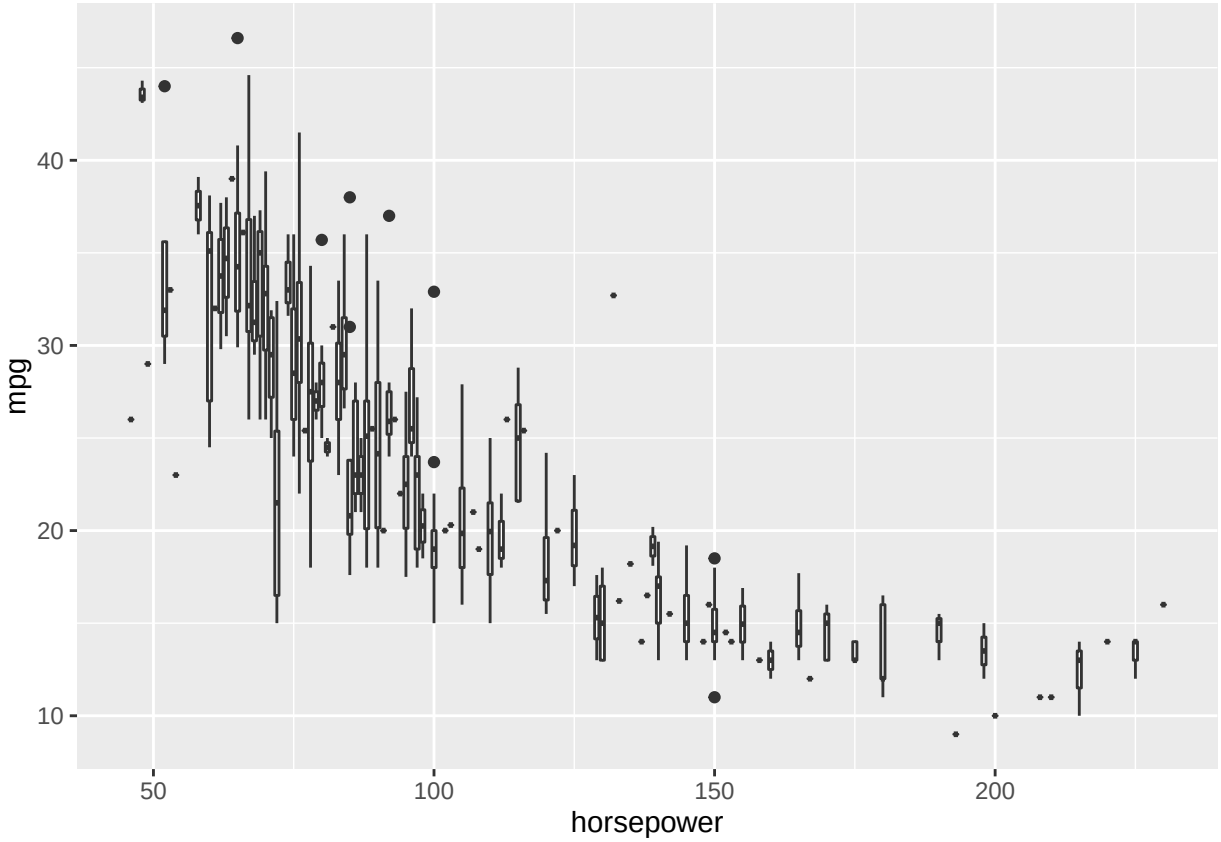


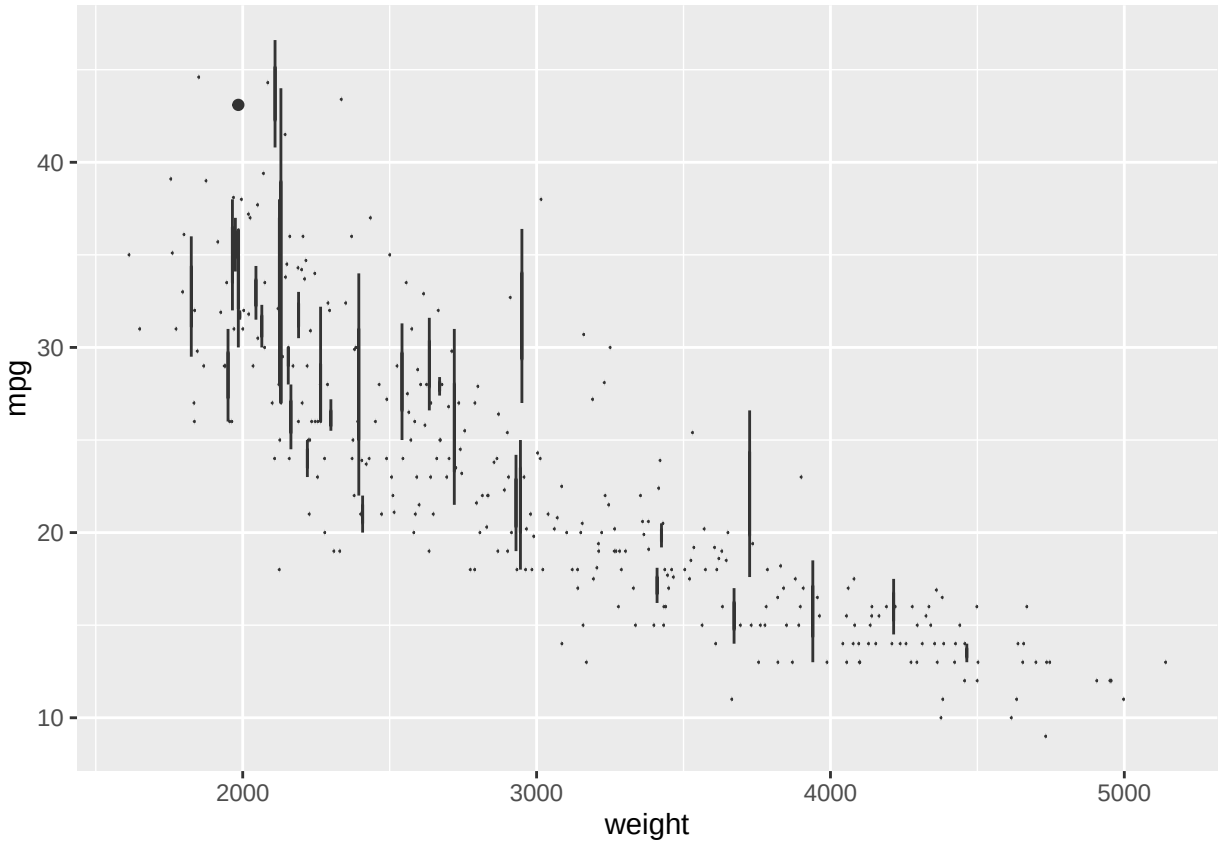
Apartado a)

Parece ser que las variables de las que más depende *mpg* son *displacement*, *horsepower* y *weight*. Veámoslas con más detalle.


mpg
displacement
horsepower
weight
Corr:
−0.805
Corr:
−0.778
Corr:
−0.832
Corr:
0.897
Corr:
0.933
Corr:
0.865


mpg
displacement





Es claro que existe una dependencia entre estas variables. Además, con el primer plot podemos ver las

correlaciones entre estas 3 variables, que es alta.

Apartado b)

Seleccionamos las variables que hemos decidido para predecir.

```
Auto.selected <- Auto[,c("displacement","horsepower","weight")]
```

Apartado c)

Como nuestro conjunto de datos es grande (392 instancias), podemos realizar un muestreo aleatorio. Así tampoco falseamos las muestras, cosa que podría pasarnos si realizamos un muestreo estratificado.

```
index <- sample(nrow(Auto), size = 0.8*nrow(Auto) )

Auto.train <- Auto.selected[index,]
Auto.test <- Auto.selected[-index,]
```

Apartado d)

Vamos a crear una nueva variable, *mpg01*, la cual tendrá 1 si el valor de *mpg* está por encima de la mediana y -1 en otro caso.

```
mpg01 <- ifelse(Auto$mpg >= median(Auto$mpg), 1, 0)
Auto.selected$mpg01 <- mpg01
Auto.train$mpg01 <- mpg01[index]
Auto.test$mpg01 <- mpg01[-index]
```

Apartado d1)

Vamos a ajustar un modelo de regresión logística para predecir *mpg01*.

```
model.LogReg <- glm(mpg01 ~ ., data = Auto.train, family = binomial)
prediction.LogReg <- predict(model.LogReg, newdata = Auto.test, type = "response")
prediction.LogReg.labels <- ifelse(prediction.LogReg > 0.5, 1, 0)
error.test <- "¿Esto cómo es?"
error.test <- sum(sign(prediction.LogReg.labels) != sign(Auto.test$mpg01)) /
                                                    length(prediction.LogReg.labels)
```

El error de test de este modelo es `8.8607595`.

Apartado d2)

Ahora vamos a ajusart un modelo k-NN.

Apartado d3)

Veamos las curvas ROC de ambos modelos.

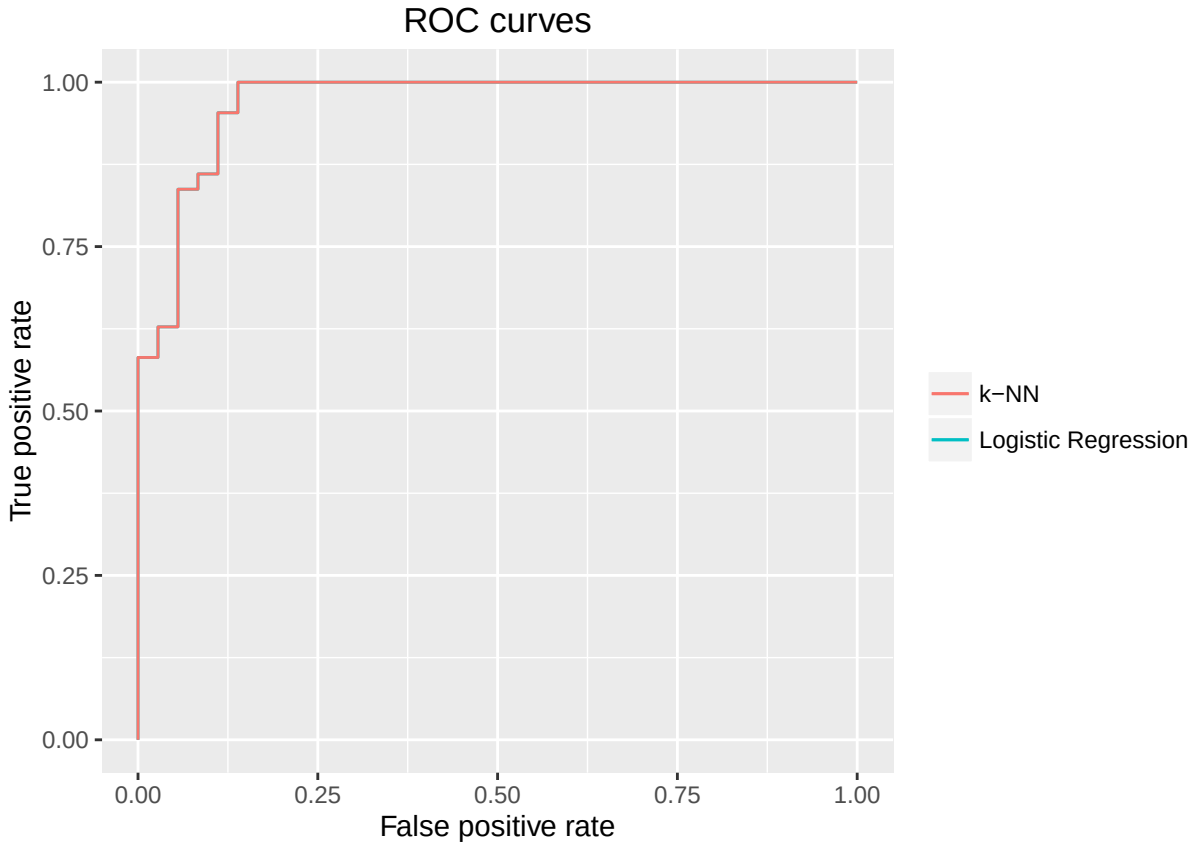
```r
roc.prediction.regLog <- prediction(prediction.LogReg, Auto.test$mpg01)
roc.performance.regLog <- performance(roc.prediction.regLog, measure = "tpr", x.measure = "fpr")

### Meter del knn

####
roc.performance.knn <- roc.performance.regLog

roc.data <- data.frame(x  = roc.performance.regLog@x.values[[1]],
                       y1 = roc.performance.regLog@y.values[[1]],
                       y2 = roc.performance.knn@y.values[[1]])

ggplot(roc.data, aes(x)) +
  geom_line(aes(y = y1, colour = "Logistic Regression")) +
  geom_line(aes(y = y2, colour = "k-NN")) +
  theme(legend.title = element_blank()) +
  labs(title= "ROC curves", x = "False positive rate", y = "True positive rate")
```




```r
auc.regLog  <- auc(roc.data$x,roc.data$y1, type = 'spline')
auc.knn     <- auc(roc.data$x,roc.data$y2, type = 'spline')
```

El área bajo la curva de la ROC de regresión logística es `0.9651519` y la del k-NN es `0.9651519`. Luego `k-NN` es el modelo que mejor *performance* tiene.

Apartado e) (Bonus-1)

Para estudiar el error con validación cruzada hacemos uso de `cv.glm`

```
model.full.LogReg <- glm(mpg01 ~ ., data = Auto.selected)
cv.LogReg <- cv.glm(data = Auto.selected, glmfit = model.full.LogReg, K = 5)
cv.LogReg$delta
```

```
## [1] 0.1043928 0.1040979
```

El error estimado es el primero de este vector. El segundo es un ajuste para compensar el sesgo introducido al no usar *Leave-One-Out*.

Para el caso del k-NN

Por tanto, vemos que es mejor *uno*.

Apartado f) (Bonus-2)

Por hacer

Ejercicio 2

Apartado a)

Ajustamos con validación cruzada sobre la variable *crim*, que es la que está en la posición 1.

```
attach(Boston)
set.seed(123456789)

index <- sample(nrow(Boston), 0.8*nrow(Boston))
Boston.full <- Boston
Boston.train <- Boston[index,]
Boston.test <- Boston[-index,]

model.Boston <- glmnet(as.matrix(Boston.train[,-1]),Boston.train[,1], alpha = 1)
```

Apartado b)

Ahora utilizamos un método LASSO y seleccionamos las variables que están por encima de un umbral.

```
cv.Boston <- cv.glmnet(as.matrix(Boston[,-1]), Boston[,1], nfolds = 5, alpha = 1)
lasso.coeff <- predict(cv.Boston, type="coefficients", s = cv.Boston$lambda.min)
threshold <- 0.1
selected <- which(abs(lasso.coeff) > threshold)[-1]
```

Con esto afirmamos que las características que superan nuestro umbral `0.1` son `4, 5, 6, 8, 9, 11, 13, 14`.

Seguir con regularización.

Apartado c)

Al igual que en el anterior apartado, definimos una nueva variable usando la mediana como umbral.

```
crim1 <- ifelse(Boston$crim > median(Boston$crim), 1, -1)
Boston.full$crim1 <- crim1
Boston.train.crim1 <- Boston.full[index,]
Boston.test.crim1 <- Boston.full[-index,]
```

Ahora ajustamos varias *SVM*, probaremos la lineal y con los núcleos disponibles, y veremos cómo se comporta cada uno. 'Ver cuál sería mejor a priori con pairs o similar'.

```
svm.linear <- svm(crim1 ~ ., data = Boston.train.crim1[,-1], kernel = "linear")
svm.linear.prediction <- predict(svm.linear, newdata = Boston.test.crim1[,-1])
confusionMatrix(sign(svm.linear.prediction), Boston.test.crim1$crim1)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction -1  1
##         -1 51 10
##         1   3 38
##
##                Accuracy : 0.8725
##                  95% CI : (0.7919, 0.9304)
##     No Information Rate : 0.5294
##     P-Value [Acc > NIR] : 1.616e-13
##
##                   Kappa : 0.7421
##  Mcnemar's Test P-Value : 0.09609
##
##             Sensitivity : 0.9444
##             Specificity : 0.7917
##          Pos Pred Value : 0.8361
##          Neg Pred Value : 0.9268
##              Prevalence : 0.5294
##          Detection Rate : 0.5000
##    Detection Prevalence : 0.5980
##       Balanced Accuracy : 0.8681
##
##        'Positive' Class : -1
##
```

```
svm.polynomial <- svm(crim1 ~ ., data = Boston.train.crim1[,-1], kernel = "polynomial")
svm.polynomial.prediction <- predict(svm.polynomial, newdata = Boston.test.crim1[,-1])
confusionMatrix(sign(svm.polynomial.prediction), Boston.test.crim1$crim1)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction -1  1
##         -1 52  8
##         1   2 40
##
##                Accuracy : 0.902
##                  95% CI : (0.8271, 0.952)
```

```
##     No Information Rate : 0.5294
##     P-Value [Acc > NIR] : 5e-16
##
##                   Kappa : 0.8019
##  Mcnemar's Test P-Value : 0.1138
##
##             Sensitivity : 0.9630
##             Specificity : 0.8333
##          Pos Pred Value : 0.8667
##          Neg Pred Value : 0.9524
##              Prevalence : 0.5294
##          Detection Rate : 0.5098
##    Detection Prevalence : 0.5882
##       Balanced Accuracy : 0.8981
##
##        'Positive' Class : -1
##
```

```
svm.radial <- svm(crim1 ~ ., data = Boston.train.crim1[,-1], kernel = "radial")
svm.radial.prediction <- predict(svm.radial, newdata = Boston.test.crim1[,-1])
confusionMatrix(sign(svm.radial.prediction), Boston.test.crim1$crim1)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction -1  1
##         -1 49  6
##         1   5 42
##
##                Accuracy : 0.8922
##                  95% CI : (0.8152, 0.9449)
##     No Information Rate : 0.5294
##     P-Value [Acc > NIR] : 3.774e-15
##
##                   Kappa : 0.7833
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.9074
##             Specificity : 0.8750
##          Pos Pred Value : 0.8909
##          Neg Pred Value : 0.8936
##              Prevalence : 0.5294
##          Detection Rate : 0.4804
##    Detection Prevalence : 0.5392
##       Balanced Accuracy : 0.8912
##
##        'Positive' Class : -1
##
```

```
svm.sigmoid <- svm(crim1 ~ ., data = Boston.train.crim1[,-1], kernel = "sigmoid")
svm.sigmoid.prediction <- predict(svm.sigmoid, newdata = Boston.test.crim1[,-1])
confusionMatrix(sign(svm.sigmoid.prediction), Boston.test.crim1$crim1)
```

```
## Confusion Matrix and Statistics
##
```

```
##           Reference
## Prediction -1  1
##         -1 22 18
##         1  32 30
##
##                Accuracy : 0.5098
##                  95% CI : (0.4089, 0.6101)
##     No Information Rate : 0.5294
##     P-Value [Acc > NIR] : 0.69044
##
##                   Kappa : 0.0319
##  Mcnemar's Test P-Value : 0.06599
##
##             Sensitivity : 0.4074
##             Specificity : 0.6250
##          Pos Pred Value : 0.5500
##          Neg Pred Value : 0.4839
##              Prevalence : 0.5294
##          Detection Rate : 0.2157
##    Detection Prevalence : 0.3922
##       Balanced Accuracy : 0.5162
##
##        'Positive' Class : -1
##
```

Analizar el error.

Apartado d) (Bonus-3)

Ajustamos con validación cruzada sobre la variable *crim*.

```
cv.Boston <- cv.glmnet(as.matrix(Boston[,-1]), Boston[,1], nfolds = 5, alpha = 1)
```

El error de validación cruzada es

```
cv.Boston$cvm
```

```
##  [1] 73.44629 69.69340 65.57450 62.15294 59.31050 56.94901 54.98697
##  [8] 53.35530 51.92575 50.57490 49.37295 48.37637 47.54303 46.84977
## [15] 46.27829 45.80756 45.42499 45.11508 44.85812 44.63284 44.44202
## [22] 44.28251 44.13463 43.99118 43.87275 43.77272 43.68583 43.61130
## [29] 43.54863 43.49150 43.41694 43.35179 43.29459 43.22690 43.17175
## [36] 43.12449 43.08471 43.03839 42.99640 42.94169 42.87580 42.82081
## [43] 42.76855 42.72311 42.68992 42.66404 42.64521 42.63186 42.62700
## [50] 42.62509 42.62654 42.62972 42.63239 42.63564 42.63938 42.64245
## [57] 42.64645 42.65055 42.65177 42.65493 42.65777 42.66085 42.66415
## [64] 42.66737 42.67058 42.67367 42.67688 42.68009 42.68274 42.68554
## [71] 42.68788 42.69060 42.69247 42.69449 42.69618 42.69745
```

Completar solución.

Ejercicio 3

Apartado a)

Ya tenemos cargado y separado el conjunto de datos en 80% training y 20% test.

Apartado b)

Vamos a ajusar un modelo de Bagging. Para ello usaremos el RandomForest y le diremos que use el total de características disponibles.

```
bagging <- randomForest(medv ~., data = Boston, subset = -index, mtray = ncol(Boston)-1, importance = T
bagging.prediction <- predict(bagging, newdata = Boston.test)
bagging.error <- "¿Esto cómo es?"
```

El error de test del modelo bagging es `¿Esto cómo es?`.

Apartado c)

Ahora vamos a ajustar un RandomForest.

```
randomFor <- randomForest(medv ~., data = Boston, subset = -index, importance = TRUE)

randomFor.error <- "¿Esto cómo es?"
```

El número de árboles usado es `500`. El error de test es `¿Esto cómo es?`.

La diferencia con bagging es . . .

Apartado d)

Ajustamos un modelo de regresión con Boosting.

```
boosting <- gbm(medv~., data = Boston.train, distribution = "gaussian")
pred <- predict(boosting, Boston.test, n.trees = 100)
boosting.error <- "¿Esto cómo es?"
```

El error de test es `¿Esto cómo es?`.

La diferencia con bagging y randomForest es. . .

Ejercicio 4

Apartado a)

Cogemos una muestra aleatoria de 800 elementos y lo usamos como training.

```
index <- sample(nrow(OJ), 800)
OJ.train <- OJ[index,]
OJ.test <- OJ[-index,]
```

Ajustamos un árbol con la variable *Purchase* como objetivo.

```
model.tree <- tree(Purchase ~ ., data = OJ.train)
```

Apartado b)

Veamos un resumen del árbol.

```
summary(model.tree)
```

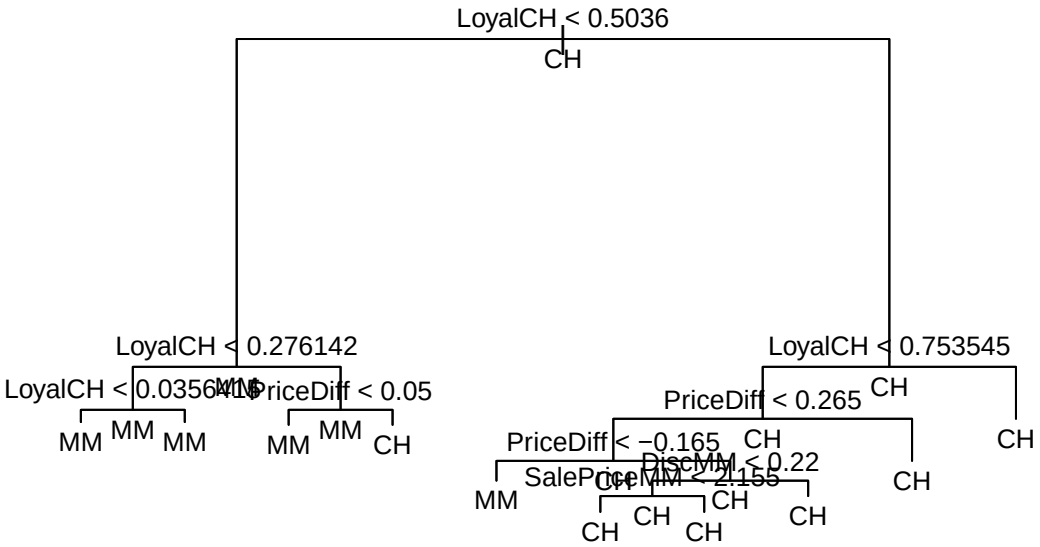
```
##
## Classification tree:
## tree(formula = Purchase ~ ., data = OJ.train)
## Variables actually used in tree construction:
## [1] "LoyalCH"     "PriceDiff"   "DiscMM"      "SalePriceMM"
## Number of terminal nodes:  10
## Residual mean deviance:  0.7312 = 577.7 / 790
## Misclassification error rate: 0.1713 = 137 / 800
```

El número de nodos terminales es de 8, y tiene un error del 16.38%. Completar.

Apartado c)

Dibujamos el árbol obtenido.

```
plot(model.tree, main="Classification tree")
text(model.tree, all=TRUE, cex=.8)
```



Interpretar.

Apartado d)

Aplicamos el árbol a nuestros datos de test.

```
prediction.tree <- predict(model.tree, OJ.test)
prediction.tree
```

```
##              CH         MM
## 13   0.95785441 0.04214559
## 16   0.95785441 0.04214559
## 19   0.53846154 0.46153846
## 20   0.53846154 0.46153846
## 27   0.95785441 0.04214559
## 30   0.95785441 0.04214559
## 31   0.53846154 0.46153846
## 43   0.95785441 0.04214559
## 44   0.95785441 0.04214559
## 46   0.95785441 0.04214559
## 48   0.95785441 0.04214559
## 50   0.95785441 0.04214559
## 55   0.95121951 0.04878049
## 67   0.95785441 0.04214559
## 71   0.26666667 0.73333333
## 74   0.95785441 0.04214559
## 78   0.95785441 0.04214559
## 93   0.53846154 0.46153846
## 104  0.95785441 0.04214559
## 105  0.50000000 0.50000000
## 106  0.95785441 0.04214559
## 110  0.95785441 0.04214559
## 111  0.95785441 0.04214559
## 113  0.95785441 0.04214559
## 116  0.95785441 0.04214559
## 122  0.95785441 0.04214559
## 124  0.95785441 0.04214559
## 133  0.95785441 0.04214559
## 134  0.95785441 0.04214559
## 137  0.95785441 0.04214559
## 141  0.50000000 0.50000000
## 142  0.53846154 0.46153846
## 149  0.18181818 0.81818182
## 151  0.18181818 0.81818182
## 157  0.95785441 0.04214559
## 159  0.95785441 0.04214559
## 160  0.95785441 0.04214559
## 162  0.95785441 0.04214559
## 165  0.95785441 0.04214559
## 169  0.95785441 0.04214559
## 176  0.95785441 0.04214559
## 177  0.95785441 0.04214559
## 178  0.95785441 0.04214559
## 180  0.95785441 0.04214559
## 182  0.95785441 0.04214559
## 183  0.95785441 0.04214559
## 194  0.95785441 0.04214559
## 198  0.95785441 0.04214559
## 199  0.95785441 0.04214559
## 209  0.95785441 0.04214559
## 210  0.95785441 0.04214559
## 212  0.95785441 0.04214559
## 213  0.95785441 0.04214559
```

```
## 218  0.95785441 0.04214559
## 220  0.95785441 0.04214559
## 223  0.18181818 0.81818182
## 228  0.53846154 0.46153846
## 231  0.26666667 0.73333333
## 234  0.96000000 0.04000000
## 239  0.95785441 0.04214559
## 240  0.95785441 0.04214559
## 245  0.95785441 0.04214559
## 246  0.95785441 0.04214559
## 247  0.95785441 0.04214559
## 248  0.95785441 0.04214559
## 250  0.95785441 0.04214559
## 256  0.18181818 0.81818182
## 264  0.50000000 0.50000000
## 265  1.00000000 0.00000000
## 267  0.96000000 0.04000000
## 269  0.53846154 0.46153846
## 276  0.01886792 0.98113208
## 279  0.01886792 0.98113208
## 280  0.01886792 0.98113208
## 281  0.01886792 0.98113208
## 291  0.01886792 0.98113208
## 294  0.01886792 0.98113208
## 301  0.53846154 0.46153846
## 302  0.26666667 0.73333333
## 310  0.53846154 0.46153846
## 311  0.53846154 0.46153846
## 312  0.50000000 0.50000000
## 315  0.95785441 0.04214559
## 318  0.95121951 0.04878049
## 320  0.53846154 0.46153846
## 326  0.53846154 0.46153846
## 330  0.53846154 0.46153846
## 332  0.26666667 0.73333333
## 334  0.18181818 0.81818182
## 335  0.18181818 0.81818182
## 337  0.18181818 0.81818182
## 338  0.18181818 0.81818182
## 342  0.95785441 0.04214559
## 344  0.95785441 0.04214559
## 346  0.95785441 0.04214559
## 349  0.95785441 0.04214559
## 354  0.26666667 0.73333333
## 358  0.53846154 0.46153846
## 359  0.53846154 0.46153846
## 360  0.50000000 0.50000000
## 368  0.18181818 0.81818182
## 369  0.18181818 0.81818182
## 370  0.53846154 0.46153846
## 373  0.53846154 0.46153846
## 376  0.53846154 0.46153846
## 378  0.18181818 0.81818182
## 379  0.18181818 0.81818182
```

```
## 385  0.18181818 0.81818182
## 392  0.18181818 0.81818182
## 405  0.18181818 0.81818182
## 410  0.53846154 0.46153846
## 412  0.26666667 0.73333333
## 414  0.18181818 0.81818182
## 425  0.53846154 0.46153846
## 426  0.26666667 0.73333333
## 429  0.53846154 0.46153846
## 431  0.18181818 0.81818182
## 434  0.26666667 0.73333333
## 435  0.26666667 0.73333333
## 436  0.53846154 0.46153846
## 438  0.26666667 0.73333333
## 441  0.95121951 0.04878049
## 442  0.95121951 0.04878049
## 443  0.95121951 0.04878049
## 449  0.50000000 0.50000000
## 452  0.53846154 0.46153846
## 460  0.26666667 0.73333333
## 468  0.95785441 0.04214559
## 475  0.18181818 0.81818182
## 488  0.50000000 0.50000000
## 490  0.95785441 0.04214559
## 493  0.95785441 0.04214559
## 507  0.95785441 0.04214559
## 518  0.95785441 0.04214559
## 519  0.53846154 0.46153846
## 521  0.96000000 0.04000000
## 525  0.26666667 0.73333333
## 530  0.96000000 0.04000000
## 544  0.18181818 0.81818182
## 549  0.18181818 0.81818182
## 563  0.50000000 0.50000000
## 574  0.18181818 0.81818182
## 577  0.95121951 0.04878049
## 580  0.53846154 0.46153846
## 582  0.95121951 0.04878049
## 603  0.95785441 0.04214559
## 607  0.95785441 0.04214559
## 608  0.95785441 0.04214559
## 609  0.95785441 0.04214559
## 611  0.95121951 0.04878049
## 615  0.96000000 0.04000000
## 618  0.95785441 0.04214559
## 620  0.95785441 0.04214559
## 621  0.95785441 0.04214559
## 632  0.96000000 0.04000000
## 633  0.26666667 0.73333333
## 634  0.95785441 0.04214559
## 637  0.95785441 0.04214559
## 638  0.95121951 0.04878049
## 647  0.95785441 0.04214559
## 649  0.95785441 0.04214559
```

```
## 655  0.95785441 0.04214559
## 663  0.53846154 0.46153846
## 666  0.26666667 0.73333333
## 669  0.18181818 0.81818182
## 680  0.26666667 0.73333333
## 682  0.18181818 0.81818182
## 687  0.18181818 0.81818182
## 688  0.18181818 0.81818182
## 696  0.01886792 0.98113208
## 705  0.01886792 0.98113208
## 712  0.01886792 0.98113208
## 717  0.01886792 0.98113208
## 719  0.01886792 0.98113208
## 721  0.01886792 0.98113208
## 722  0.01886792 0.98113208
## 723  0.01886792 0.98113208
## 725  0.01886792 0.98113208
## 726  0.01886792 0.98113208
## 727  0.01886792 0.98113208
## 731  0.26666667 0.73333333
## 732  0.26666667 0.73333333
## 737  0.26666667 0.73333333
## 738  0.53846154 0.46153846
## 739  0.53846154 0.46153846
## 744  0.26666667 0.73333333
## 747  0.26666667 0.73333333
## 748  0.18181818 0.81818182
## 755  0.26666667 0.73333333
## 756  0.53846154 0.46153846
## 757  0.53846154 0.46153846
## 761  0.53846154 0.46153846
## 762  0.50000000 0.50000000
## 766  0.95785441 0.04214559
## 772  0.53846154 0.46153846
## 775  0.18181818 0.81818182
## 777  0.96000000 0.04000000
## 781  0.95121951 0.04878049
## 782  0.50000000 0.50000000
## 796  0.18181818 0.81818182
## 799  0.50000000 0.50000000
## 806  0.95121951 0.04878049
## 807  0.95121951 0.04878049
## 818  0.95785441 0.04214559
## 819  0.95785441 0.04214559
## 825  0.95785441 0.04214559
## 831  0.95785441 0.04214559
## 838  0.26666667 0.73333333
## 840  0.18181818 0.81818182
## 841  0.18181818 0.81818182
## 842  0.53846154 0.46153846
## 846  0.18181818 0.81818182
## 850  0.53846154 0.46153846
## 856  0.95785441 0.04214559
## 858  0.95785441 0.04214559
```

```
## 859  0.95785441 0.04214559
## 867  0.96000000 0.04000000
## 871  0.96000000 0.04000000
## 874  0.53846154 0.46153846
## 878  0.95785441 0.04214559
## 881  0.95785441 0.04214559
## 886  0.26666667 0.73333333
## 888  0.95121951 0.04878049
## 891  0.53846154 0.46153846
## 892  0.95121951 0.04878049
## 902  0.95785441 0.04214559
## 904  0.95785441 0.04214559
## 906  0.18181818 0.81818182
## 910  0.53846154 0.46153846
## 913  0.53846154 0.46153846
## 924  0.26666667 0.73333333
## 925  0.26666667 0.73333333
## 926  0.26666667 0.73333333
## 931  0.18181818 0.81818182
## 934  0.26666667 0.73333333
## 935  0.18181818 0.81818182
## 937  0.18181818 0.81818182
## 944  0.01886792 0.98113208
## 946  0.01886792 0.98113208
## 947  0.01886792 0.98113208
## 950  0.01886792 0.98113208
## 951  0.01886792 0.98113208
## 957  0.26666667 0.73333333
## 969  0.53846154 0.46153846
## 970  0.26666667 0.73333333
## 974  0.26666667 0.73333333
## 978  0.18181818 0.81818182
## 981  0.26666667 0.73333333
## 992  0.26666667 0.73333333
## 993  0.26666667 0.73333333
## 994  0.53846154 0.46153846
## 998  0.95121951 0.04878049
## 1001 0.26666667 0.73333333
## 1005 0.18181818 0.81818182
## 1008 0.18181818 0.81818182
## 1013 0.95785441 0.04214559
## 1014 0.95785441 0.04214559
## 1015 0.95785441 0.04214559
## 1016 0.95785441 0.04214559
## 1021 0.95785441 0.04214559
## 1027 0.95785441 0.04214559
## 1032 0.95785441 0.04214559
## 1040 0.26666667 0.73333333
## 1045 0.95785441 0.04214559
## 1048 0.95785441 0.04214559
## 1051 0.95121951 0.04878049
## 1056 0.26666667 0.73333333
## 1058 0.53846154 0.46153846
## 1068 0.95121951 0.04878049
```

```
## 1070 0.95121951 0.04878049
```

Valorar resultados.

Apartado e)

Aplicamos la función cv.tree() a los datos de training y veamos qué hace.

```
model.cv.tree <- cv.tree(model.tree, K = 5)
model.cv.tree
```

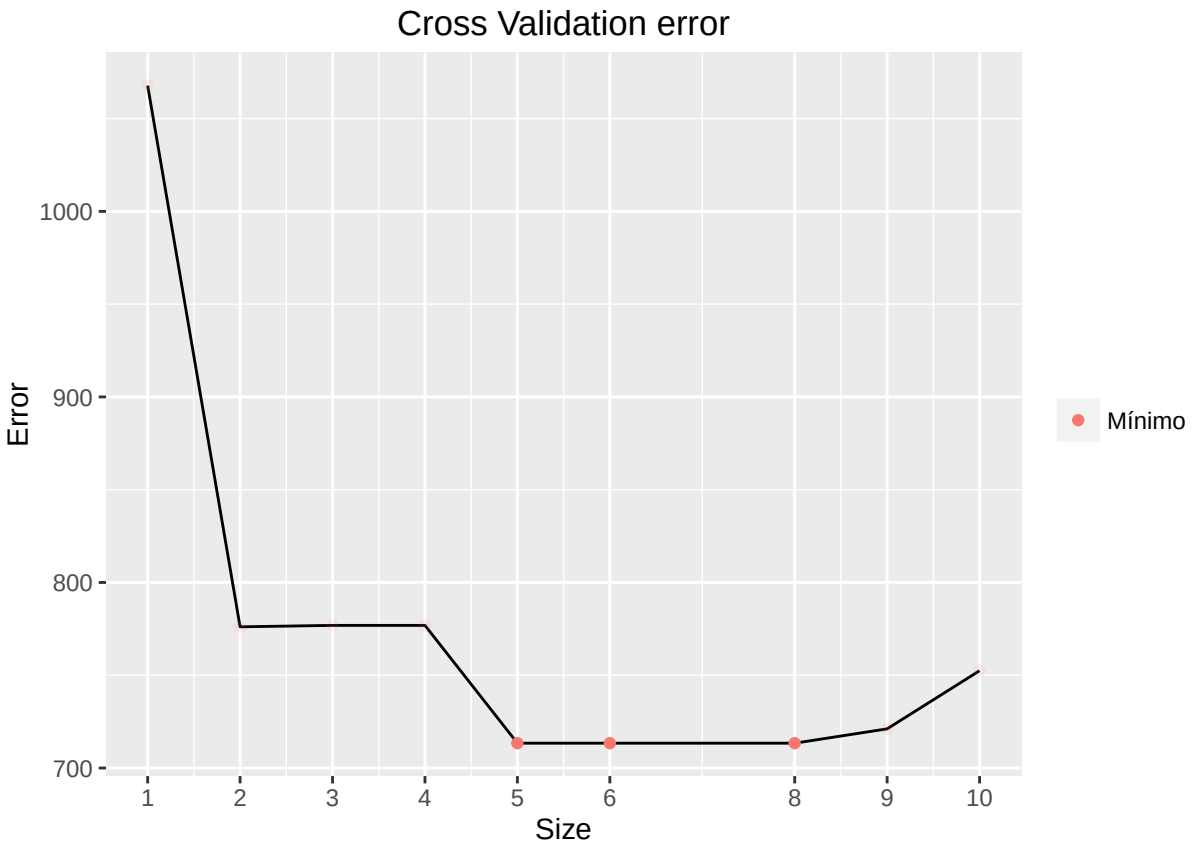
```
## $size
## [1] 10  9  8  6  5  4  3  2  1
##
## $dev
## [1]  752.4366  721.1024  713.3778  713.3778  713.3778  776.8580  776.8580
## [8]  776.0987 1067.7919
##
## $k
## [1]      -Inf  11.00549  13.51258  14.02312  17.78698  37.79043  38.60387
## [8]  46.64903 294.32466
##
## $method
## [1] "deviance"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

Apartado f) (Bonus-4)

```
error.tree <- data.frame(size = model.cv.tree$size,
                         error = model.cv.tree$dev)

error.tree$alpha <- ifelse(error.tree$error == min(error.tree$error), 1, 0)

ggplot(error.tree, aes(x=size,y=error)) + geom_line() +
  geom_point(aes(colour = "Mínimo", alpha = alpha )) +
  scale_x_continuous(breaks = error.tree$size) +
  guides(alpha=FALSE) +
  theme(legend.title = element_blank()) +
  labs(title = "Cross Validation error",
       x = "Size",
       y = "Error")
```



Podemos ver que el mínimo de error se alcanza en `8, 6, 5`.